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Learning from experience or learning from others? Inferring informal training from a human capital earnings function with matched employer–employee data

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Abstract

A model of informal training which combines learning from own experience and learning from others is proposed in this paper. It yields a closed-form solution that revises Mincer–Jovanovic's [Mincer, J., Jovanovic, B., 1981. Labor mobility and wages. In: Rosen, S. (Ed.), Studies in Labor Markets. Chicago University Press, Chicago, pp. 21–64] treatment of tenure in the human capital earnings function. We estimate the structural parameters of this non-linear model on a large French cross-section with matched employer–employee data. We find that workers on average can learn from others 10% of their own human capital on entering one plant, and catch half of their learning from others' potential in just 2 years. The private marginal returns to education are declining with education as more educated workers have less to learn from others and share the social returns of their own education with their less qualified co-workers. The potential for learning from others on the job varies across jobs and establishments, and this provides a new distinction between imitation jobs and experience jobs. Workers in imitation jobs, who learn most from others, tend to have considerably longer tenure than workers in experience jobs. Although workers in experience jobs can learn little from others, we find that they learn a lot by themselves. We document several analogies between the imitation jobs/experience jobs "dualism" and the primary/secondary jobs and firms' dualism implied by the dual labor market theory. However, our binary classification of jobs depicts the data more closely than the dual theory

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categorization into primary-type and secondary-type establishments. Competition prevails between jobs and firms but jobs differ by their learning technology.

JEL classification: J24; J31; I2

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1. Introduction

The effects of human capital on earnings are commonly captured by a remarkably simple equation, which was suggested and estimated by Mincer (1974) on US census data and is still known as the "Mincerian" earnings function. The most widely estimated version of this model is linear in education and quadratic in labor market experience: it is usually called the quadratic earnings function. An extended version of this equation, which was proposed by Mincer and Jovanovic (1981), also includes a quadratic function of tenure in the incumbent firm. The Mincerian earnings function has been efficient in extracting valuable information about the costs and returns of education and training from experience-earnings profiles. The recent availability of large matched employer–employee data sets in a number of countries (Abowd and Kramarz, 1999) makes it worth asking how this popular tool could be extended to extract additional information about the amount and structure of informal learning on-the-job. A natural direction of research was advocated by Mincer (1974) himself:

> "[...] the most important and urgent task is to refine the specification of the post-school investment category [...] to include details (variables) on a number of forms of investment in human capital."

As a matter of fact, matched worker–firm data yield valuable information about co-workers and firms' training policy which makes it possible to separate learning from others and learning from own experience. This should contribute to a better understanding of the processes of human capital accumulation used by firms and of firms' heterogeneity in this respect. We shall be using here a unique French cross-section on labor cost and wages structure (INSEE 1992) comprising 150,000 wage earners in 16,000 establishments.

Much of the informal training taking place on-the-job may be captured by a combination of learning from own experience (or, self-learning) and learning from others (or, learning by watching). Barron et al. (1989) confirm the importance of these informal learning processes in the US. In the 3 months following the recruitment of new workers, 96% of on-the-job training is given to them in an informal way by other workers (145.2 h of a total 151.1 h) and more than one-third of on-the-job training (53.1 h) is provided through a "learning by watching" process. Learning by oneself through experience and learning from others seem to capture the essential ingredients of informal learning on-the-job, so that a model that incorporates these two elements should offer a good description of informal on-the-job training. They both form the microeconomic counterparts of the autonomous and catch-up growth processes separated by Benhabib and Spiegel (1994) in macroeconomic growth models, following a suggestion of Nelson and Phelps (1966).

The model of informal on-the-job learning from self and others (LSO) presented in Section 2 has the nice feature of yielding a closed-form solution.[1] Hence, it is possible to identify its structural parameters with matched employer–employee data and infer from the latter the characteristics of informal training within jobs and firms, like the relative use of both learning technologies, the complementarity or substitutability of education and training, the magnitude of spillover effects of human capital among co-workers and social rates of return to education. The data and econometric approach are then discussed in Section 3. Section 4 compares the econometric estimates of the non-linear LSO earnings equation with those derived from Mincerian polynomials in tenure (linear, quadratic or quartic) and interprets the results. Since the potential for learning from others is a novel distinguishing feature between jobs and establishments in our analysis, Section 5 examines the heterogeneity of jobs and establishments along this new dimension. This exercise provides a new partition of jobs by their learning technology: learning from own experience in *experience jobs* and learning from others in *imitation jobs*. These two types of jobs are contrasted and the correspondence between the imitation jobs/experience jobs “dualism” and the primary/secondary jobs and firms' dualism implied by dual labor market theory (Doeringer and Piore, 1971; Dickens and Lang, 1985) is questioned. The summary of findings and conclusions will be found in Section 6.

2. Informal learning on-the-job from self and others: theory

Workers may acquire job-specific training, which is assumed to be general (i.e. transferable to other firms in the same job), either formally or informally. Both kinds of training are costly as they take time away from more productive tasks. The main difference between them seems to be that purely informal learning, unlike formal training, does not consume any resources from other workers.[2] As a result, employees who are getting or supplying informal training are not always conscious that they are doing so.[3] In further contrast to investments in schooling and formal training, the supply of informal training is tied into the workers' labor contract. As Rosen (1972) remarked long ago, each firm provides a specific package of (informal) training services to its workers so that the latter, once they entered a firm, have no other choice than to acquire its knowledge. Consequently, workers will bear the costs of their informal training and reap the returns. In addition, we assume the existence of two informal learning technologies on-the-job: learning from own experience (or, self-learning) and learning from others (or, learning by watching). “Self-learning” on-the-job enhances productivity by a trial-and-error process. The complementarity of education and experience and the propensity of the more qualified workers to adopt innovations faster (Schultz, 1975) suggest that this is a multiplicative process. Watching the more productive workers do their own jobs also increases the productivity of a less productive worker by a simple imitation process, at no cost for her “teachers”. This is a kind of externality which, for two main reasons, does not call for a direct compensation of the teachers. First, it is a diffuse process in which many teachers may interact with many students without even realizing

[1] This model extends a model of learning by watching (LBW) presented by Lévy-Garboua (1994), by incorporating self-learning or learning from experience. Previous tests of the LBW model on various data sets have appeared in Chennouf et al. (1997), Nordman (2000), and Destré (2003).

[2] Like formal training, informal training consumes non-labor resources of the firm. When non-labor costs can be neglected, informal training is freely supplied by firms if workers under training pay for the foregone value of their own time.

[3] This is consistent with the finding (Barron et al., 1997) that employees underestimate the amount of informal training they received by 20% relative to employers.

that they supply training services, as they suffer no cost. Second, today's students will normally become tomorrow's teachers and so repay what they received in the past.

2.1. The earnings function

In the Mincerian tradition, wage rates are assumed to equal the value of marginal product of labor on a competitive market. Thus, gross earnings reflect human capital. Let us designate tenure in the incumbent firm as t, expressed in discrete time ($t = 0, 1, \ldots$), and job-specific human capital of worker i in firm and job j by the end of period t as h_{ijt}. With these notations, the notation h_{ij0} represents the level of job-specific human capital on entering the firm, that is, after x periods of experience on the labor market in *other* firms. Total experience of work is $x + t$. Worker i interacts with other workers from the same firm and job j but she acquires existing knowledge from those who possess more knowledge than herself. If knowledge is homogeneous, let H_{ijt} be the highest level of job-specific human capital embodied in an employee that she is exposed to and can learn from in the same firm. It summarizes the firm's knowledge as far as worker i is concerned, that is, the human capital of worker i's "teacher". By definition, we have: $H_{ijt} \geq h_{ijt}$. The combined effects of own experience and learning from others on a worker's productivity in period t are assumed additive in the small and given by

$$h_{ijt} - h_{ij,t-1} = gh_{ij,t-1} + \frac{n}{1+n}(H_{ij,t-1} - h_{ij,t-1}) \quad \text{for} \quad t \geq 1 \tag{1}$$

In this equation, the effect of self-learning is proportional to the stock of human capital when the period begins. The factor g is net of the physical depreciation rate of human capital and it is assumed to be constant. It might be negative if the rate of depreciation exceeded the constant rate of self-learning, but we expect it to be normally positive. While experience tends to increase the human capital of all workers at a constant rate, the presence of others is presumably more beneficial to less qualified workers who have a lot to learn, if n ($n > 0$), the rate of knowledge diffusion within the firm, is identical for all workers. For simplicity, this assumption will be kept here.[4] Moreover, n is invariant with respect to tenure.

The recurrence Eq. (1) can be solved after postulating that the structure of job-specific knowledge (human capital) and the diffusion process within the firm are time-invariant. Proofs are given in Appendix A. By also assuming that the firm's knowledge grows with experience at the constant rate g, it is shown that job-specific human capital grows with tenure in the following way:

$$h_{ijt} = (1+g)^t[k^t h_{ij0} + (1-k^t)H_{ij0}] \quad \text{with} \quad k = \frac{1+g(1+n)}{(1+g)(1+n)} \quad (0 < k < 1) \tag{2}$$

Eq. (2) may also be written as

$$h_{ijt} = (1+g)^t h_{ij0}[1 + (1-k^t)\lambda_{ij}] \quad \text{with} \quad \lambda_{ij} = \frac{H_{ij0}}{h_{ij0}} - 1 \quad (\lambda_{ij} \geq 0) \tag{3}$$

The term λ_{ij} designates the job-specific *learning from others' potential*, which is independent of tenure. Eqs. (2) and (3) form the basis of the LSO model. They boil down to the LBW

[4] This is actually not a serious problem if we hypothesize that the rate of knowledge diffusion depends solely on the schooling level, which remains constant over lifetime. This is indeed a plausible assumption because it is the role of education to enhance the ability to learn, not that of on-the-job training. Lévy-Garboua et al. (2004) develop a theory of educational systems based on this distinction.

(learning by watching) model proposed by Lévy-Garboua (1994) if $g = 0$. In general, the human capital of any given worker increases with tenure and converges towards the firm's job-specific knowledge. However, the latter is a moving target, which increases at a steady rate through experience.

For the purpose of econometric estimation, we convert Eq. (3) in natural logarithms. If g is small, we get:

$$\log h_{ijt} = \log h_{ij0} + gt + \log[1 + \lambda_{ij}(1 - k^t)] \tag{4}$$

If what can be learned from others in the current firm is a small share of the worker's initial stock of human capital, (4) can be further simplified and approximated by

$$\log h_{ijt} = \log h_{ij0} + gt + \lambda_{ij}(1 - k^t) \quad \text{with} \quad \lambda_{ij} \cong \log \frac{H_{ij0}}{h_{ij0}} \tag{5}$$

Eq. (5) is a testable form of the LSO gross earnings function. The logarithm of gross earnings is the sum of a linear-in-tenure experience effect and an exponential effect of learning from others that converges fast towards the firm's job-specific learning potential. Once the latter is specified, both learning effects can be identified with Eq. (5).

2.2. The returns to tenure

The (gross) marginal returns to tenure for a worker i employed in firm and job j (R_{ijt}) are defined as

$$R_{ijt} = \frac{h_{ijt} - h_{ij,t-1}}{h_{ij,t-1}} \quad \text{for} \quad t \geq 1$$

After a few manipulations with the help of (3), we get:

$$R_{ijt} = g + \frac{n}{1+n}\left(\frac{\lambda_{ij}k^{t-1}}{1 + \lambda_{ij}(1 - k^{t-1})}\right) \tag{6}$$

This equation highlights that one part of the returns to tenure is firm dependent.[5] A worker benefits from the firm which employs her, in addition to what she gets from experience, insofar she can learn something from other workers in her job category. This prediction of the model evokes one part of the dual theory story that tells that the returns to tenure are nil in secondary-type jobs, in which practically no human capital accumulation takes place, while they are positive in primary-type jobs (Dickens and Lang, 1985). Indeed, (6) indicates that the returns to tenure are minimal and reduce to g whenever $\lambda_{ij} = 0$, i.e. $H_{ij0} = h_{i0}$, that is, when there is no scope for learning from others on-the-job. However, in the present model, the crucial distinction between primary-type jobs and secondary-type jobs does not bear on their respective levels of human capital but on the *teacher/worker knowledge ratio* in the firm from the standpoint of each worker (i.e., H_{ij0}/h_{ij0}). The latter is obviously idiosyncratic, depending upon the tasks to be performed and personal abilities.

[5] We avoid saying here that returns to tenure are firm-specific because what we have to say is entirely consistent with general training.

The marginal returns to tenure are shown by Eq. (6) to be a concave increasing function of the job-specific learning potential:

$$\frac{\partial R_{ijt}}{\partial \lambda_{ij}} > 0, \qquad \frac{\partial^2 R_{ijt}}{\partial \lambda_{ij}^2} < 0$$

It is also straightforward to show that (6) exhibits a convex decreasing relation of the marginal return to tenure with tenure:

$$\frac{\partial R_{ijt}}{\partial t} < 0, \qquad \frac{\partial^2 R_{ijt}}{\partial t^2} > 0$$

The quadratic earnings function implies a linearly decreasing curve. Thus, it is not supported by what seems a reasonable description of informal learning processes at work on-the-job. Mincer (1974) remarked that a Gompertz curve might yield a better fit than the simple quadratic function. More recently, Murphy and Welch (1990) noticed that the quadratic curve underestimates the marginal return to tenure at low and very high values of tenure, and they recommended a quartic earnings function. The steep decline of R_{ijt} with tenure is responsible for the alternating sign of $\partial R_{\mathrm{ijt}}/\partial_n$: initially positive at low values of tenure (including $t = 1$), and eventually negative. Increasing the efficiency of learning from others on-the-job will benefit low-tenured workers who will learn faster, but it will reduce what remains to be learned from others in the future.

Finally, it can be shown that:

$$\frac{\partial R_{ijt}}{\partial g} \geq 1, \quad \text{for} \quad t \geq 2 \quad \text{and} \quad \lambda_{ij} \geq 0 \quad (= 1 \text{ if } \lambda_{ij} = 0)$$

Increasing the efficiency of experience initially increases the self-learning effect but this will provoke a multiplier effect in subsequent periods by raising the firm's knowledge.

3. Data and econometric specification

3.1. The data

We use in this paper a large French cross section with matched employer–employee data, the 1992 INSEE survey on labor cost and wages structure. The latter contains information about 150,000 workers across 16,000 establishments.

This survey of labor costs is carried out concurrently in all European Union countries every 4 years, and aims to provide comparable labor market statistics across EU countries. For the 1992 wave of this survey, INSEE matched the data with those on the structure of wages (as the subject matter of the two surveys was obviously similar). The population covered by these data is very broad, including establishments of all sizes and of all industries (which rules out agriculture, fisheries, non-traded services, central and local government).

For the regression analysis, we constructed a number of variables. These include the total number of years of education, total potential experience in the labor market (age – number of years of education – 6), hourly earnings (gross salary plus payments in kind, all divided by the number of paid hours over the year), and the average number of paid hours of training per worker in the establishment (the weighted average of the number of hours of paid training by worker by occupational category (executive or non-executive) divided by the total number of workers by occupational category).

As for the education variable, since available information was the highest paper certificate held by the worker, we had to determine the theoretical number of years of education per worker. To do this, we calculated the median number of years of education (which is less sensitive to outliers) for each qualification considered, using a sub-sample of more than 8000 workers from the same survey for whom the number of years of education was available. This indirect method for calculating the length of education has the advantage of partially removing the endogeneity of the education variable.

Table 1 summarizes the acronyms and a definition of the main variables used in the empirical analysis, and provides descriptive statistics.

3.2. Econometric specification

Before estimating the earnings function (5), we need to specify how h_{ij0} and λ_{ij} are related to observables. The specification of establishments' job-specific learning potential rests on the empirical definitions of the worker's job ladder and of the worker's most qualified teacher. In the present paper, we adopt a binary division of jobs into "executive" and "non executive" jobs.[6] The latter is known without error for all workers, and determines an exogenous partition of job ladders in French plants. However, even with a partition of workers between jobs, the worker's most qualified teacher cannot be identified as a single co-worker of the same category when knowledge is heterogeneous. Indeed, workers can learn different skills from different co-workers who have more skill-specific human capital than themselves. In order to deal with skill heterogeneity, we define worker i's "representative teacher" as a fictitious worker endowed with S_{ij} years of education, X_{ij} years of experience in other firms, and T_{ij} periods of tenure in the incumbent firm and job j, such that: $S_{ij} \geq s_i$, $X_{ij} \geq x_{ij}$, $T_{ij} \geq 0$. Then we define the human capital of both the worker (h_{ij0}) and her most qualified teacher (H_{ij0}) when the worker entered plant j (hence, with zero tenure) by the earnings predicted by *the same* quadratic (in experience and tenure) earnings function:

$$\log H_{ij0}(S_{ij}, X_{ij}, T_{ij}) = a_0 + a_1 S_{ij} + a_2 X_{ij} + a_3 X_{ij}^2 + a_4 T_{ij} + a_5 T_{ij}^2 \tag{7}$$

with $a_1, a_2, a_4 > 0$ and $a_3, a_5 < 0$, and

$$\log h_{ij0}(s_i, x_i, t_{ij} \equiv 0) = a_0 + a_1 s_i + a_2 x_i + a_3 x_i^2 \equiv \log h_{i0} \tag{8}$$

Let $z_{ij} \equiv (s_i, x_i, t_{ij})$ and $Z_{ij} \equiv (S_{ij}, X_{ij}, T_{ij})$ denote the human capital vectors of i and her representative teacher in establishment and job j. The teacher's characteristics are unobservable in our data,[7] but we do observe the same variables on a random sample of employees from the same job and establishment. Since individuals can only learn from more qualified workers in the same job category, a minimal assumption for recovering the unknown characteristics of worker i's teacher on-the-job is to assume that they lie between the establishment maximum and individual values of the latter at some fixed relative position, then approximate the true maximum by the sample's maximum. Letting $Z_j = \sup_{i \in j} z_{ij}$ be the maximum *observable* value for the characteristic z in the

[6] This corresponds to the French statutory distinction of "cadres" and "non cadres", loosely captured by the English words "executives" and "non executives". Such distinction plays a precise role in the calculation of payrolls and it divides all workers in two lifelong categories in the vast majority of cases.

[7] Such observation would require a description of student–teacher interactions within establishments.

Table 1
Descriptive statistics

Symbol	Definition	Mean	Minimum	Maximum	S.D.
h_{ijt}	Hourly earnings	69.48	29.00	395.83	39.49
hours_i	Number of hours paid work per year	1671.78	33	2310	585.46
sex_i	1 for men; 0 for women	0.60			
age_i	Age	37.68	16	65	10.30
nat_i	1 if French; 0 otherwise	0.93			
mar_i	1 if married; 0 otherwise	0.61			
cont_i	1 if open-ended contract; 0 otherwise or no answer	0.86			
exec_i	1 if executive; 0 otherwise	0.11			
s_i	Number of years of schooling	12.77	8	18	1.65
x_i	Number of years of labor market experience (outside of the current establishment)	9.27	0	49	8.72
t_{ij}	Number of years of tenure	9.27	0	46	8.84
N	Number of observations	137,211			
S_j	Highest level of education among workers of the same establishment	14.26	10	18	1.92
X_j	Highest level of former experience among workers of the same establishment	26.88	0	49	9.34
T_j	Highest level of tenure among workers of the same establishment	16.58	0	46	10.32
reg_j	1 if Paris; 0 otherwise	0.16			
size_j	Size of the establishment	140.16			540.46
union_j	1 if trade union representatives reported in the establishment; 0 otherwise	0.25			
eval_j	1 if individual productivity evaluation procedures reported in the establishment; 0 otherwise	0.20			
coop_j	1 if cooperation among workers reported; 0 otherwise	0.49			
shift_j	1 if workers shifting to other jobs in the establishment reported; 0 otherwise	0.16			
wagind_j	1 if wage increases reported as being mainly individualized; 0 otherwise	0.20			
twagind_j	1 if tenure reported as being very important for setting the individualized wage increase; 0 otherwise	0.06			
pwagind_j	1 if worker's productivity gains reported as being very important for setting the individualized wage increase; 0 otherwise	0.35			
trwagind_j	1 if worker's training efforts reported as being very important in setting the individualized wage increase; 0 otherwise	0.08			
expwagind_j	1 worker's experience reported as being very important in setting the individualized wage increase; 0 otherwise	0.16			
fortrain_j	Average annual hours of paid formal training per worker in the establishment	11.83	0	1748.37	53.73
J	Number of establishments	14,693			

establishment's sample, we write:

$$Z_{ij} = \beta_z Z_j + (1 - \beta_z) z_{ij} \quad \text{with} \quad 0 \leq \beta_z \leq 1 \tag{9}$$

The coefficient β_z indicates the relative distance which separates the average worker from her most qualified teacher. It takes a value of zero if there is no opportunity for learning from others and one if the most qualified teacher always coincides with the most qualified worker of the establishment's sample. By subtracting (8) from (7), we get an estimate of the learning potential from others for each worker i in plant and job j:

$$\lambda_{ij} \cong \log \frac{H_{ij0}}{h_{i0}} = a_1 \beta_s (S_j - s_i) + a_2 \beta_x (X_j - x_i) + a_3 \beta_x^2 (X_j - x_i)^2 + 2a_3 \beta_x (X_j - x_i) x_i + a_4 \beta_t T_j + a_5 \beta_t^2 T_j^2 \tag{10}$$

Reporting (8) and (10) into (5), we then obtain for individual i in establishment and job j a *non-linear* gross earnings equation,[8] to which we add an error term u_{ijt}:

$$\begin{aligned} \log h_{ijt} = {} & a_0 + a_1 s_i + a_2 x_i + a_3 x_i^2 + g t_{ij} + (a_1 \beta_s (S_j - s_i) + a_2 \beta_x (X_j - x_i) \\ & + a_3 \beta_x^2 (X_j - x_i)^2 + 2a_3 \beta_x (X_j - x_i) x_i + a_4 \beta_t T_j + a_5 \beta_t^2 T_j^2) \\ & \times \left(1 - \left(\frac{1 + g(1+n)}{(1+g)(1+n)}\right)^{t_{ij}}\right) + \sum_k \delta_k c_{ijk} + u_{ijt} \end{aligned} \tag{11}$$

where c_{ijk} is a column vector of control variables and δ_k is a row vector of coefficients associated with each of these variables. Among the controls, several variables describe the wage and training policy of the firm and one measures the average amount of formal training provided by the establishment to the worker's job category. Thus our estimates are likely to capture informal training. The non-linear structure of this equation permits identification of most structural parameters of learning: g, n, a_1, a_2, a_3, β_s, β_x. We estimate (11) using non-linear least squares (NLSQ). Since the above expression assumes that the magnitude of the learning potential is small and we cannot be sure that this approximation is valid, we also estimated the exact formula (not reported here).

With cross-section data and a non-linear model, we cannot account for unobserved individual or firm heterogeneity in the manner of Abowd et al. (2000). Besides, the large number of establishments in our data set rules out the possibility of controlling for firm heterogeneity by introducing a dummy variable for each establishment into Eq. (11). In order to temper the effects of unobserved individual and firm heterogeneity which might bias the estimated coefficients, we added a large number of control variables to our regression.[9] We checked that the latter capture a good deal of

[8] We follow common practice by estimating the gross earnings equation rather than net earnings. The latter equation accounts for the fact that workers bear the cost of their general training. We also estimated the net earnings equation (results not shown) and got very similar results with a slightly better fit.

[9] With the exception of log hours, the control variables are in discrete form and include the following (the reference category is in parentheses): sex (women), occupation (non-executives) and region (all regions with the exception of Paris and its suburbs), 3 dummies for nationality (French), 5 dummies for marital status (married), 3 dummies for labor contract (open-ended contract), 1 dummy for the presence of trade union representatives in the establishment (no), 3 dummies for the presence of individual productivity evaluation procedures in the establishment (yes), 4 dummies for the presence of incentives for cooperation among co-workers, 3 dummies for the presence of systematic job turnover among workers of the establishment (no), 5 dummies for the degree to which wage increases are being individualized (little), 5 dummies for the importance of tenure for setting the individualized wage increase (none), 5 dummies for the importance of worker's

the establishment heterogeneity by estimating the quadratic-in-tenure earnings function, which is linear in its parameters, both with establishment fixed effects (without the controls) and with the controls only. The comparison of the marginal returns to education, former experience and tenure exhibited little difference between these two estimates. By adding the sample's maximum values of education, former experience and tenure in the Mincerian equation, since they are included in the non-linear model, these differences were further reduced (results not shown). To account for the fact that within establishment observations are not independent, which will not bias the estimates of the parameters but is likely to produce standard errors that are much smaller than they should be, we have to use an appropriate method (Moulton, 1990). Unfortunately, the non-linear nature of our model precludes the use of off-the-shelf techniques. However, we can assume that this issue is minor since the standard errors would need to be understated by a factor higher than 4.05 in order for them to be insignificant at the 1% level, which is very unlikely. Indeed, when we compare the results of the quartic-in-tenure earnings function (with and without clustering method), the standard errors are never increased by a factor higher than 1.8.

4. Informal learning on-the-job from self and others: results

4.1. Earnings functions and the private and social returns to education

Table 2 presents the estimated parameters of the earnings function incorporating learning from self and others (LSO) along with four other models of earnings. Three versions of the Mincerian model appear in the first three columns of the table: linear in tenure (column 1), quadratic in tenure (column 2), and quartic in tenure (column 3). Moreover, the pure learning-by-watching model (LBW) is shown in column 4. All of the estimated Mincerian equations are linear in education and quadratic in former experience. The adjusted R^2 is equal to 60.41% for our model. All of the main explanatory variables are significant at the 1% level in all equations. Among the Mincerian earnings functions, we confirm on the present data that the quartic function of tenure yields a better fit than the usual quadratic and the linear equation. Moreover, the function that incorporates learning from self and others (LSO, in column 5) clearly has a better fit than the two nested models of column 1 ($n = 0$) or column 4 ($g = 0$). Finally, the simpler version of LSO described by (11) has been estimated in column (6). The approximation is shown to be valid since the structural parameters reported in columns (5) and (6) are remarkably similar.

The omission of learning from experience would lead to a severe underestimation of the knowledge diffusion parameter, since n goes from 45.22% in column 5 to 5.75% in column 4. It is more intuitive to compare the time required for a worker to learn share α of the firm's knowledge as far as she is concerned. From Eq. (2), we derive:

$$\frac{H_{ijt} - h_{ijt}}{H_{ij0} - h_{i0}} = \left(\frac{1 + g(1 + n)}{1 + n}\right)^t$$

The time required for learning share α of the firm's knowledge is computed by equating the first member with $1 - \alpha$ and solving for t. The results of these computations are given in Table 3

productivity gains for setting the individualized wage increase (very high), 5 dummies for the importance of worker's training efforts for setting the individualized wage increase (average), 5 dummies for the importance of worker's experience for setting the individualized wage increase (average), 4 dummies for average number of paid hours of formal training in the establishment over the past year (no hours of training), 12 industry dummies (traded services) and 6 establishment size dummies (less than 20 workers).

Table 2
Estimated parameters of earnings functions (dependent variable: log of hourly earnings)[a]

Parameters	(1) Linear in t	(2) Quadratic in t	(3) Quartic in t	(4) LBW[b]	(5) LSO[c]	(6) LSO[c,d]
Coefficient of s_i	0.05293a (0.00052)	0.05283a (0.00052)	0.05260a (0.00052)	0.05841a (0.00056)	0.06060a (0.00058)	0.06055a (0.00058)
Coefficient of x_i	0.01031a (0.00026)	0.01013a (0.00026)	0.01024a (0.00026)	0.01635a (0.00056)	0.01352a (0.00033)	0.01357a (0.00033)
Coefficient of x_i^2	−0.00021a (8.40E−06)	−0.00020a (8.39E−06)	−0.00021a (8.38E−06)	−0.00034a (0.00001)	−0.00027a (9.69E−06)	−0.00027a (9.69E−06)
Coefficient of t_{ij}		0.01992a (0.00028)	0.03912a (0.00096)			
Coefficient of t_{ij}^2		−0.00022a (9.27E−06)	−0.00243a (0.00011)			
Coeficient of t_{ij}^3			0.00008a (5.13E−06)			
Coefficient of t_{ij}^4			−9.70E−07a (7.18E−08)			
β_s				0.38352a (0.01298)	0.26172a (0.00805)	0.26176a (0.00808)
β_x				0.95666a (0.02101)	0.21489a (0.01202)	0.21862a (0.01207)
Coefficient of T_{ij}				0.02142a (0.00056)	0.00377a (0.00030)	0.00377a (0.00029)
Coefficient of T_{ij}^2				−0.00036a (0.00001)	−0.00007a (6.92E−06)	−0.00007a (6.92E−06)
n				0.05755a (0.00197)	0.45220a (0.03822)	0.46631a (0.03826)
g	0.01344a (0.00010)				0.01077a (0.00018)	0.01074a (0.00018)
Constant	3.08839a (0.01210)	3.10714a (0.01209)	3.12898a (0.01211)	3.00232a (0.01249)	3.00543a (0.01256)	3.00580a (0.01256)
Adjusted R^2	0.5888	0.6004	0.6018	0.6021	0.6041	0.6041
N	137,211	137,211	137,211	137,211	137,211	137,211

[a] Standard errors are in parentheses and a, b and c mean, respectively, statistically significant at the 1%, 5% and 10% levels.
[b] LBW, learning by watching.
[c] LSO, learning from self and others.
[d] Simplified version of LSO.

Table 3
Knowledge diffusion and teacher/worker knowledge ratio[a]

	Knowledge diffusion parameter n (%)	Tenure for catching 50% of job knowledge (year)	Tenure for catching 95% of job knowledge (year)	Teacher/worker knowledge ratio
LSO	45.22	1.93	8.37	1.10 (0.0001)
LBW	5.75	12.38	53.53	1.45 (0.0005)

LSO, learning from self and others; LBW, learning by watching.
[a] Standard errors are in parentheses.

Table 4
Marginal returns to education and former experience (in %)

	Mincerian quadratic in t	Learning from self and others (LSO)
Education	5.28	4.61
Former experience	0.62	0.73

for the two values $\alpha = 0.50$ and $\alpha = 0.95$. There is a huge difference between the two models and the estimations yielded by the LSO earnings function make a lot more sense. *On average*, *it takes 1.93 years for a worker to embody 50% of what she can learn from others in her establishment*, *and 8.37 years to embody 95% of this total*. Moreover, the average worker of our sample, who has 9.27 years of tenure, has already learned 96% of what she can learn from others. The omission of self-learning would greatly underestimate the speed with which individuals learn from others, as we have just seen; but, on the other hand, it would greatly overestimate the potential for learning from others.

Table 3 reports that a worker can learn 10% of her initial human capital on average from co-workers in the same establishment and job, while the estimate derived from the LBW model is 45%. Table 2 also indicates that the relative distance which separates the average worker from her most qualified teacher (β_z) is equal to 0.26 in terms of educational capital and 0.21 in terms of former experience capital. These two values are well inside the [0, 1] interval and considerably lower than their LBW counterparts. β_s declines from 0.38 to 0.26, and β_x from 0.95 to 0.21 between columns 4 and 5 in Table 2. The omission of self-learning would have the mechanical effect of raising the estimated value of H_{ij0}/h_{i0}, hence of the β parameters.

The Mincerian earnings function is a convenient tool for estimating the average returns to education and market experience. The private return to education is then simply given by the coefficient of the length of schooling. The estimates drawn from the quadratic model are reported in Table 4 and compared with those from the LSO equation in Table 2. The marginal return to education (computed at the average length of schooling in the sample) is only 4.61% instead of 5.28% for the Mincerian model. Moreover, it decreases with the length of education in our model because, the more education, the less can be learned from others. The fact that investments in education and learning from others are substitutes has generally been overlooked in previous studies which emphasized the complementarity of education and self-learning.[10] However,

[10] The more educated workers receive more formal training (e.g. Destré et al., 1999) and learn more by themselves informally (see Eq. (1)). However, when we tested the hypothesis that education increase the individual's ability to learn *from others* on-the-job n, we could not find any significant positive effect.

Table 5
Schedule of marginal rates of return to tenure (%) for selected years of tenure[a,b]

Model	Mincerian quadratic in t	Mincerian quartic in t	Learning from self and others (LSO)
First year of tenure	1.98	3.74	4.50a (0.0046)
Second year of tenure	1.94	3.29	3.35a (0.0030)
Third year of tenure	1.89	2.88	2.60a (0.0019)
Fourth year of tenure	1.84	2.52	2.11a (0.0013)
Fifth year of tenure	1.80	2.21	1.78a (0.0009)
Mean tenure	1.61	1.32	1.22a (0.0001)

[a] The number of observations is 119,667 since the returns to tenure are only defined for $t \geq 1$.
[b] Standard errors are in parentheses and a, b and c mean, respectively, statistically significant at the 1%, 5% and 10% levels.

using a different empirical approach than ours, Green et al. (2001) also found that less educated workers make up for their lower education through more work-based learning. Our study assumes both complementarity of experience with education and substitution of imitation for education.

In addition, the rate of return of education on the wages of less qualified co-workers can be estimated from the LSO model by taking the derivative of $\log h_{ijt}$ with respect to S_j in Eq. (11). On our sample, it is worth 0.67% (at mean tenure value), that is, 14.5% of the private marginal return to education. This result contributes to the emerging literature on education spillovers within firms (e.g. Battu et al., 2003; Martins, 2004; Moretti, 2004). It is worth noticing that, in the LSO model, the coefficient of the length of schooling is the sum of the private rate of return to education and of the education spillovers on less qualified co-workers, that is, the "social" rate of return to education. Thus our estimate of the social rate of return to education is 6.06%.

4.2. Firm's knowledge and the returns to tenure

Table 5 and Fig. 1 show the schedule of gross marginal rates of return to tenure which derives from the present model of on-the-job learning (computed from Eq. (6)) and compare the latter with estimates drawn from two Mincerian earnings functions (quadratic and quartic in tenure).

The marginal rate of return, computed for the sample's mean tenure, is equal to 1.22%, which is significantly positive and greater than the constant rate of return to self-learning on-the-job,[11] $g = 1.07\%$. The difference of 0.15% measures the average increase which can be attributed to learning-by-watching. Thus nearly 12% of what is learned informally on-the-job emanates from others and 88% is the result of self-learning. However, the respective shares of these two kinds of learning are very unequally distributed over time. While the rate of return from self-learning remains constant, the benefits from imitating others are mainly reaped by workers shortly after being hired and they are very large then. For instance, Table 5 shows that earnings rise by 4.50% in the first year of tenure and only 1.78% in the fifth year. Learning-by-watching accounts for three-quarters of the marginal rate of return in the first year, but this proportion falls to 49% in the fifth year and so on. The rate of return estimated by the present model is significantly

[11] This parameter should mainly capture returns to informal training since we control for the average number of hours of formal training in the establishment over the last year by occupational group (in two broad categories).

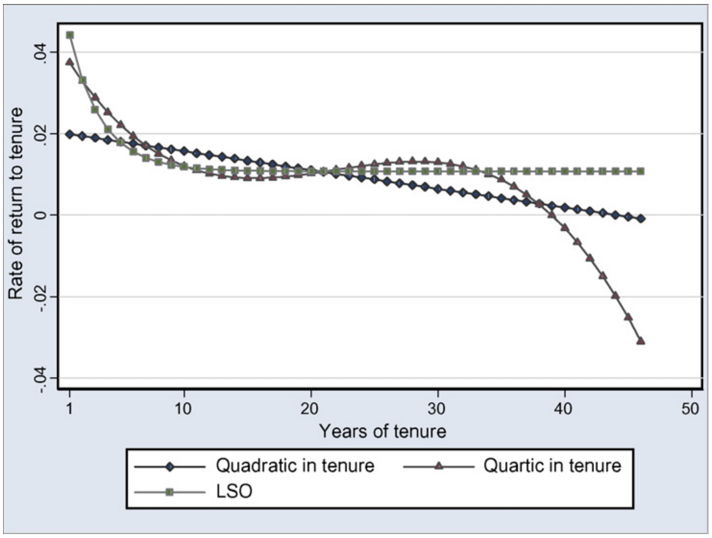

Fig. 1. Schedules of marginal rates of return to tenure for three earnings functions.

higher (by a *t*-test of Student) than what is predicted by the quadratic earnings function both at low and very high tenure. Fig. 1 shows that a quartic function of tenure fits our model fairly well as long as tenure do not exceed 30 years or so. However, the rates of return predicted by the LSO equation are slightly higher than the quartic in the first 2 years and decline more sharply.

5. Job heterogeneity

5.1. Imitation jobs and experience jobs

The present model of on-the-job learning in combination with the matched employer–employee data that we use enables us to compute the individual-specific teacher/worker knowledge ratio of the establishment. Although the average teacher/worker knowledge ratio of firms, H_{ij0}/h_{i0}, is estimated to be 1.10 (see Table 3), which is significantly different from one (by a *t*-test), there is substantial heterogeneity between jobs and firms. The distribution of teacher/worker knowledge ratio has a mode at 1.0512 and a median which is very close to the mean around 1.10. Mainly for illustration purposes, we divide jobs in two categories: *imitation jobs* which offer more than the modal opportunities for learning from others (i.e. $\lambda_{ij} > 1.0512$) and *experience jobs* which offer no more than the modal opportunities for learning from others on-the-job (i.e. $\lambda_{ij} \leq 1.0512$). The great majority of jobs are imitation jobs and only 15.8% of jobs are classified as experience jobs. Workers in experience jobs presumably learn relatively more by themselves, that is, through their own experience on the job. Since little can be learned from others on experience jobs, the schedule of marginal rates of return to tenure is expected to be low for these jobs, and so effective tenure must be low as well. Table 6 shows the average and marginal returns to tenure (calculated at the mean point of tenure, see Table 1), teacher/worker knowledge ratio and effective tenure in experience and imitation jobs, respectively. The average rate of return is given for a 5-year tenure which fits the observed durations in both types of job. The average worker in imitation jobs can

Table 6
Returns to tenure (%) in experience and imitation jobs[a,b]

	Average return at 5 years	Marginal return at mean tenure	Marginal return at mean tenure of job	Teacher/worker knowledge ratio	Mean tenure in job
Experience jobs	8.14a (0.0071)	1.13a (0.0001)	1.28a (5.62E−04)	1.03 (0.0001)	5.44 (0.0393)
Imitation jobs	14.50a (0.0103)	1.24a (0.0001)	1.14a (7.15E−05)	1.12 (0.0001)	11.51 (0.0276)
Total	13.58a (0.0109)	1.22a (0.0001)	–	1.10 (0.0001)	10.63 (0.0250)

[a] The number of observations is 119,667 since the returns to tenure are only defined for $t \geq 1$.

[b] Standard errors are in parentheses and a, b and c mean, respectively, statistically significant at the 1%, 5% and 10% levels.

learn 12% of her initial job-specific human capital from others and has 11.51 years of tenure while the average worker in experience jobs can only learn 3% from others and only has 5.44 years of tenure. Thus *tenure is considerably lower in experience jobs than in imitation jobs*, and the difference is found highly significant by a *t*-test. The correlations between firm's relative job-specific knowledge and tenure, or imitation job (a dummy) and tenure, are both positive and highly significant (by a *t*-test) with values of 0.382 and 0.246, respectively. The potential for learning from others is definitely a major determinant of job stability and this conclusion does not depend on the knowledge being firm-specific as commonly assumed by human capital theory (Becker, 1964; but see Rosen, 1972). The average rate of return to tenure at 5 years is also markedly lower (by a *t*-test) in experience jobs, i.e. 8.14% versus 14.50%. Finally, the difference in marginal rates of return to tenure R_{ijt} in the imitation and experience jobs is positive by a difference *t*-test.

So far, the description of jobs having a low potential for learning from others (experience jobs) is somewhat similar to that of jobs belonging to the "secondary sector" of the dual theory of labor (Doeringer and Piore, 1971; Dickens and Lang, 1985). By contrast, jobs offering a high potential for learning from others (imitation jobs) are similar to jobs of the "primary sector". Thus it is natural to ask whether this is more than an analogy and reflects some kind of labor market dualism with a rationing of primary-type jobs. Job competition is expected to equalize the marginal rates of return between jobs, while job rationing in the primary sector would cause marginal rates of return to be higher in the rationed segment of the job market. Column 3 compares the marginal returns to tenure in the primary-type and secondary-type jobs (computed at the average tenure of sector). Experience (secondary-type) jobs do not appear less profitable than imitation (primary-type) jobs on the margin. Therefore, our categorization of jobs by their learning from others' potential manifests no form of labor market dualism and is consistent with unrestrained competition on the job market.

5.2. *Dualism at the establishment's level?*

The foregoing analysis applies to jobs, that is, to specific employer–employee matches. Do the same conclusions hold when jobs are aggregated at the establishment level? This question deserves to be raised because the dual theory of labor was originally set at the firm's level (Doeringer and Piore, 1971) and disaggregated data are often lacking below the firm's or establishment's level. Therefore we now calculate the mean teacher/worker knowledge ratio on the sample of workers in each establishment and draw the frequency distribution of this mean across establishments. The mode of this new distribution is 1.0710 while the mean and median are around 1.08. *Firms* with a low potential for learning from others on average will be defined as those for which the mean teacher/worker knowledge ratio does not exceed 1.0710, and will be said to form the

Table 7
Returns to tenure (%) and the dual labor market at the plant's level[a,b]

	Average return at 5 years	Marginal return at mean tenure	Marginal return at mean tenure of job	Teacher/worker knowledge ratio	Mean tenure in job
Experience plants	9.06a (0.0162)	1.63a (0.0055)	1.24a (8.34E−04)	1.04 (0.0002)	6.54 (0.0721)
Imitation plants	13.61a (0.0233)	1.85a (0.0068)	1.17a (2.80E−04)	1.11 (0.0003)	10.64 (0.0552)
Total	11.88a (0.0241)	1.76a (0.0048)	–	1.08 (0.0003)	9.08 (0.0468)

[a] The number of observations is 119,667 since the returns to tenure are only defined for $t \geq 1$.
[b] Standard errors are in parentheses and a, b and c mean, respectively, statistically significant at the 1%, 5% and 10% levels.

"secondary sector". Table 7 extends the information displayed by Table 6 at the establishment's level, and the same conclusions can be reached at first sight. However, on closer inspection of the employer–employee matches, the picture is partly modified by the aggregation. While education has a significantly negative (by a *t*-test) correlation (−0.293) with firm's teacher/worker knowledge ratio at the job's level, the correlation turns significantly positive (by a *t*-test) and small (0.031) at the establishment's level. The rationale behind this surprising result is that, although more educated individuals have less to learn from others on their job since they know more, they choose firms offering greater opportunities for learning because they are willing to invest more in training. As the firm-level effect more than offsets the job-level effect, the aggregation of jobs in one establishment conceals the equalizing effect of learning from others. Moreover, since a large majority of jobs offer good opportunities for learning from others, the aggregation of jobs within establishments greatly magnifies the positive correlation of the potential for learning from others (measured by teacher/worker knowledge ratio) with observed earnings: it rises from −0.016 to 0.173 (statistically significant by a *t*-test). Thus predictions of the dual theory of labor regarding the employer–employee match at the establishment's level mainly result from the aggregation of jobs within establishments. Other implications of dual labor theory are also captured by our simple typology of sectors. For instance, 50% of workers employed in imitation jobs versus only 14% of workers in experience jobs belong to establishments which have trade union representatives. Besides, 33% of imitation (primary-type) establishments have trade union representatives versus 12% of experience (secondary-type) establishments. However, the inspection of column 3 in Table 7 reveals that the marginal returns to tenure computed at the average tenure of sector are no smaller in secondary-type than in primary-type establishments. This finding confirms the job-level description in Table 6, and rules out the existence of rationing by primary-type establishments which is central in dual labor market theory. Therefore, our distinction between imitation jobs and experience jobs depicts the data more closely than the dual theory categorization into primary-type and secondary-type establishments. Competition prevails between jobs and firms but jobs differ by their learning technology. Firms that make an intensive use of learning from others adhere rather naturally to more collective forms of workers' governance such as reliance to trade unions in comparison with those that make an intensive use of self-learning.

5.3. Learning from jobs or learning from firms?

In this section, we seek to validate the new distinction between imitation jobs and experience jobs by comparing their respective earnings profiles. Table B.1 (shown in Appendix B) summarizes the estimates from our LSO model for each job type. We can check that there is no potential for learning from others in experience jobs since β_s, β_x and the coefficients of T_{ij} and T_{ij}^2 are never

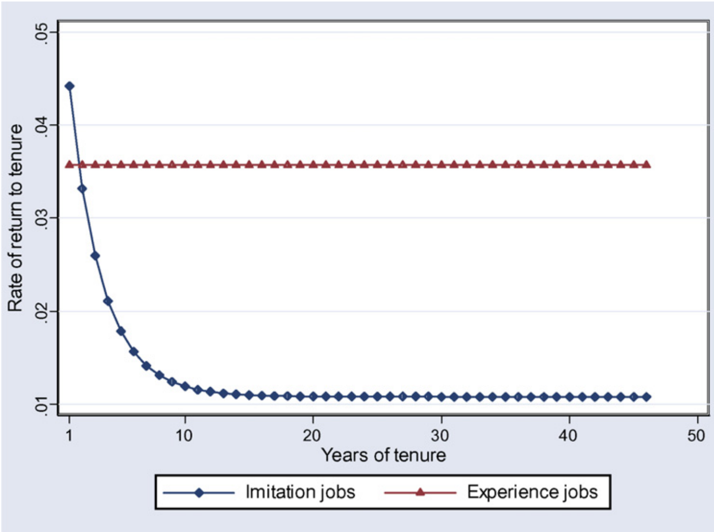

Fig. 2. Schedules of marginal rates of return to tenure for imitation and experience jobs.

significant at the 1% level for these jobs. By contrast, the same coefficients are highly significant for imitation jobs. In addition, we get the striking result that *the average marginal rate of return to self-learning is considerably higher for experience jobs than for imitation jobs*: 3.56% versus 1.10%. Workers with experience jobs can learn little from others but, on average, they learn a lot by themselves. Rather than learning from their firm, so to speak, they essentially learn from their job. This last finding legitimates our terminology and distinction of two learning technologies: imitation and (own) experience. A parallel can be drawn between learning technologies for jobs and information technologies for goods (Nelson, 1970). Like inspection goods, imitation jobs can almost be discovered before doing the job. By contrast, like experience goods, experience jobs must be discovered on the job.

Fig. 2 contrasts the steeply declining schedule of marginal rates of return to tenure for imitation jobs with the flat schedule for experience jobs. In imitation jobs, earnings rise by 5.60% in the first year of tenure and by 1.87% in the fifth year. After a little more than 2 years, earnings begin to rise more slowly in imitation jobs than in experience jobs. Workers learn half of what they can learn from others in an imitation job in just 1.72 years, and 95% in 7.42 years. Since average tenure reaches 11.51 years for imitation jobs, this means that workers stay in their job more than 5 years after they have practically stopped learning from others. However, a fraction of the older and more experienced workers ends up in experience jobs. The sample's mean age is 41 in experience jobs and 37 in imitation jobs; the sample's mean former experience (before entering the current firm) is 17.48 years in experience jobs and only 7.73 years in imitation jobs. Table 8 demonstrates that

Table 8
Marginal returns to education and former experience (%) for imitation and experience jobs

	Imitation jobs	Experience jobs
Education	4.70	5.35
Former experience	0.76	0.35

the marginal returns to education are lower in imitation jobs, as more educated workers have less to learn from others, while the marginal returns to former experience are lower in experience jobs as the latter are occupied by more experienced workers.

6. Summary and conclusions

We have suggested a simple model of informal learning on-the-job which combines learning from (own) experience and learning from others. This yields a closed-form solution that revises the Mincer–Jovanovic's (1981) treatment of tenure in the human capital earnings function by relating earnings to the individual's job-specific learning potential. We estimated the structural parameters of this non-linear model on a large French cross-section with matched employer–employee data. We find that workers on average can learn from others 10% of their own human capital on entering the firm, and catch half of their learning potential in just 2 years. Since individuals learn fast from their co-workers, the estimated returns to tenure loom larger than predicted by a quadratic, or even a quartic-in-tenure, Mincerian function in the first years and decline more sharply (until about 30 years). Learning by watching accounts for three quarters of the marginal rate of return in the first year of tenure, but this share falls rapidly, with an average of 12%. While education and self-learning on-the-job are complementary, education and learning from others on-the-job are substitutes. The more education, the less can be learned from others. This forces the private marginal return curve to decline with education, an effect which was not captured by current theory. Seen from a different perspective, the more educated workers share the social returns of their own education with their less qualified co-workers.

The potential for learning from others on the job varies across jobs and establishments, and this provides a new distinction between imitation jobs and experience jobs. Workers in imitation jobs, who learn most from others, tend to have considerably longer tenure than workers in experience jobs. The latter are more mobile and have accumulated more market experience. Although workers in experience jobs can learn little from others, we find that they learn a lot by themselves. Consequently, we do not find a close correspondence between the imitation jobs/experience jobs "dualism" and the primary/secondary jobs and firms' dualism implied by the dual labor market theory. Even though imitation jobs imply far less turnover than experience jobs, imitation jobs do not appear to be "better" in terms of education levels and wages. We show, however, that predictions of the dual labor market theory which cannot be observed at the job's level under our classification of jobs emerge from the aggregation of jobs at the establishment level. Furthermore, we find no evidence of rationing of primary-type jobs and establishments. Competition prevails between jobs and firms but jobs differ by their learning technology. Firms that make an intensive use of learning from others adhere rather naturally to more collective forms of workers' governance such as reliance to trade unions in comparison with those that make an intensive use of self-learning.

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Appendix A. Derivation of the LSO earnings function

Eq. (1) can be written (omitting everywhere the *ij* under scripts for exposition):

$$h_t = \left(g + \frac{1}{1+n}\right) h_{t-1} + \frac{n}{1+n} H_{t-1}$$

If $g = 0$, i.e. in the pure learning-by-watching case, h_t would be simply a weighted average of h_{t-1} and H_{t-1}. Putting $(1 + g)$ in factor, we get:

$$h_t = (1+g)\left[\frac{1+g(1+n)}{(1+g)(1+n)} h_{t-1} + \frac{n}{(1+g)(1+n)} H_{t-1}\right]$$
$$= (1+g)[kh_{t-1} + (1-k)H_{t-1}]$$

After writing that the firm's job-specific knowledge grows with experience if the distribution of job-specific knowledge is maintained constant within the firm:

$$H_t = (1+g)H_{t-1}$$

we derive Eq. (2) by recurrence from these expressions of h_t and H_t.

Appendix B

Estimated parameters of earnings functions for imitation and experience jobs are given in Table B.1.

Table B.1
Estimated parameters of earnings functions for imitation and experience jobs[a]

Parameters	Imitation jobs	Experience jobs
Coefficient of s_i	0.06221a (0.00062)	0.05352a (0.00160)
Coefficient of x_i	0.01346a (0.00037)	0.01188a (0.00087)
Coefficient of x_i^2	−0.00027a (0.00001)	−0.00024a (0.00002)
β_s	0.24555a (0.00780)	4.08519b (1.90614)
β_x	0.18558a (0.01167)	1.17015 (1.32452)
Coefficient of T_{ij}	0.00481a (0.00031)	−0.06007 (0.09122)
Coefficient of T_{ij}^2	−0.00008a (7.18E−06)	−0.00989 (0.00651)
n	0.52292a (0.04285)	0.02684a (0.00844)
g	0.01106a (0.00017)	0.03568a (0.00769)
Constant	3.04613a (0.01376)	2.95352a (0.03208)
Adjusted R^2	0.6114	0.5885
N	115,481	21,730

[a] Standard errors are in parentheses and a, b and c mean, respectively, statistically significant at the 1%, 5% and 10% levels.

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